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Complexity Management for the Start-up in Lithium-ion Cell Production

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Abstract

This paper presents the core of a quality management methodology for production chain optimization, applicable from early design stages of production systems to the production start-up, as well as its application in lithium-ion cell production. The entire methodology was presented before [1]. The results of the methodology's first step, which is based on process Failure Mode and Effects Analysis (FMEA), are briefly described since the collected correlations are the input for the further steps. This paper describes how these correlations are transferred into correlation matrices and then propagated over the entire production chain by means of multiple domain matrices (MDM). The resulting production chain MDM provides parameters with direct or indirect influences on the quality parameters of the final product. Furthermore, relevant parameters are selected by an iterative application of MDM based production chain analyses in combination with Pareto analysis and experimental investigations. Proceeding steps quantify the identified influences and derive set point values for the individual processes by means of a multivariate optimization of the final cell quality considering the entire production chain.

Selection and peer-review under responsibility of the International Editorial Committee of the "2nd International Conference on Ramp-Up Management" in the person of the Conference Chair Prof. Dr. Robert Schmitt

Keywords: Production engineering; Quality Management; Batteries

1. Introduction

In the short and medium term lithium-ion cells are the most promising technology for electrochemical energy storage systems in electric vehicles [2, 3] as well as for stationary storage systems [4]. Compared to consumer cells in both applications exist higher quality requirements, especially regarding life time and safety issues, and different conditions of operation, leading to adapted production processes and systems. Additionally, quality relevant effects of production processes are mostly unknown. On the one hand, this is caused by the lack of available information about production related quality investigations. On the other hand, the production chain of lithium-ion cells is complex [1] due to the multiplicity of processes, their diversity and partial time dependency, the high number of relations as well as due to unknown effects of process influences on product quality. Furthermore, the complexity of the process chain is accompanied by time-consuming quality assurance, which represents a further challenge in cell manufacturing. Consequences of the complexity in lithium-ion cell production are over-engineering and uncertain requirements in the design of production systems, high scrap rates in cell production as well as extensive acceptance tests for cell customers.

In order to reduce production costs of lithium-ion cells and battery systems facing the described challenges, a methodology for the quality planning of complex production chains for battery cells was developed [1]. The investigated process chain with its 19 processes for lithium-ion cell production, implemented at the Institute of Machine Tools and Industrial Management (*iwb*), as well as a novel method for the identification of cause-and-effect chains were introduced. In this paper the subsequent steps of the methodology are specified and again applied to lithium-ion cell manufacturing.

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2. Quality Planning of Complex Production Chains for Battery Cells

By means of the FMEA-based method for quality parameter identification a broad data basis for the further application of the methodology was acquired. The developed expert survey tool was extensively applied and intermediate states of expert information were evaluated with the support of the MDM based methods described in the following chapter. By means of iterations in the expert surveys, gaps as well as dead-end branches in the cause-and-effect chains could be identified and systematically questioned in expert workshops. With this procedure more than 2.100 cause-and-effects in lithium-ion cell production provided from 12 cell design and production experts were acquired, representing a presumably complete mapping of the real cell production in terms of quality relevant cause-and-effect chains.

This paper can be subdivided in two major chapters: chapter 3 presents the method for quality parameter classification, which deals with the evaluation of the cause-and-effects provided by the FMEA tool and their relations in the production chain by means of MDM. Chapter 5 explains the method for quality parameter selection, an iterative procedure consisting of theoretical and experimental steps for the selection of quality relevant parameters. Both methods employ MDM as a backbone and as a storage for the cause-and-effect information. While the MDM is set up for the entire production chain with the method for quality parameter classification, it is continuously updated by applying the method for quality parameter selection.

3. Method for Quality Parameter Classification

3.1. Overview and Structure

The method for quality parameter classification computes direct and indirect cause-and-effects in the entire production chain, taking all raw material properties, input product properties, process parameters, disturbance quantities, intermediate product properties and quality features of the final product into account. These parameters and their direct correlations are provided by the method of quality parameter identification. They represent the interface to the production chain wide investigations described in this paper. First, these data is evaluated in order to obtain correlation matrices for each process as pictured in Figure 1. These matrices contain the following quantities, which qualitatively describe cause-and-effect relations respectively the subjectivity of expert knowledge [1]: severity B and the according level of confidence of its evaluation S_B as well as the probability A and the according level of confidence S_A, all with value margins from 0 to 3. Second, the MDM is built with the information about the production chain structure and filled with the values in the correlation matrices. Afterwards, a path search reveals the indirect cause-and-effect correlations in process chain with influence on the final product quality features. Finally, direct and indirect correlations are classified resulting in a MDM based cause-and-effect model of the production chain, which is the interface to the subsequent method for quality parameter selection.

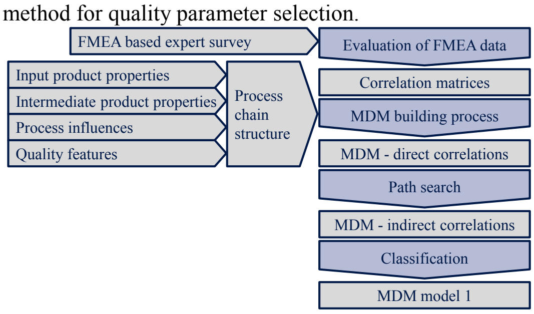

Figure 1: Structure of the method for quality parameter classification

3.2. Evaluation of the FMEA data

As a first step of the FMEA data evaluation mean values were calculated, if one cause-and-effect correlation was assessed by more than one expert. This was the case for approximately 30 % of the collected correlations. In case of the levels of confidence, a simple mean value was computed according to equation 1, where n represents the number of expert opinions:

$$S_X = \frac{\sum_{i=1}^{n} S_{X,i}}{n}, X \in \{A, B\} \quad (1)$$

In case of the severity and the probability values, the according level of confidence of the expert opinion was also considered (equation 2). Consequently, confident expert opinions dominate compared to unconfident opinions.

$$X = \frac{\sum_{i=1}^{n} (X_i \cdot S_{X,i})}{\sum_{i=1}^{n} S_{X,i}}, X \in \{A, B\} \quad (2)$$

Using the mean values of A, B, S_A and S_B correlation matrices for each process and for each of the value types were generated. The rows of these matrices consist of the potential causes and the columns of the potential effects enlisted in the FMEA in each process. Also matrices containing the information about the interactions between the causes were generated for each process.

3.3. MDM building process

For the computation of cause-and-effect correlations over the entire production chain a MDM [5] was employed. MDMs are able to map different relationship types within a domain and between different domains. In particular, it is able to derive indirect dependencies for certain applications [5, 6]. A MDM is defined as a combination of Design Structure Matrices (DSM) [7, 8] and Domain Mapping Matrices (DMM) [9]. MDMs were mainly applied in product design [10-15]. However, some applications in production processes exist. For example a MDM was employed to model product and production concepts on different abstraction levels and to connect the product concept with the production concept in early design stages [16]. Furthermore, a welding process analysis focused on the influence of the welding sequence on distortion using a DSM was conducted [17]. The elements were categorised in domains and so a MDM was generated. With this approach indirect dependencies between the welding sequence and distortion by means of the figure *locality* [5] of the node *distortion* were computed. Since the node *welding sequence* is not directly linked to the node *distortion,* elements which connect these two nodes were identified and taken into account for the deduction of welding rules.

MDM was not yet applied to entire production chains and no method for deriving indirect dependencies over several domains is known. Since MDM is a powerful tool to analyse complex systems, e.g. in product design as shown above, it was applied to the production chain of lithium-ion cells. The main objective was to compute all indirect cause-and-effect chains in cell production influencing the final product quality, based on direct correlations derived from the FMEA survey. For this reason, the correlation matrices for each process, which are output of the FMEA-based method for quality parameter identification, were transformed into one MDM for the entire production chain. As can be seen in Figure 2, the arrangement of the MDM domains is defined according to their occurrence in the production chain. The domains are further divided in three layers. The first layer is the domain itself, whereas the second layer consists of the category names which were also used in the FMEA-based expert survey for the selection of parameter categories. The third layer lists the specific properties, which appear in the FMEA in the rows *cause* and *effect*. This structure is exemplary shown in Figure 2 for the domain *input product properties*, where x represents a random process number within the production chain.

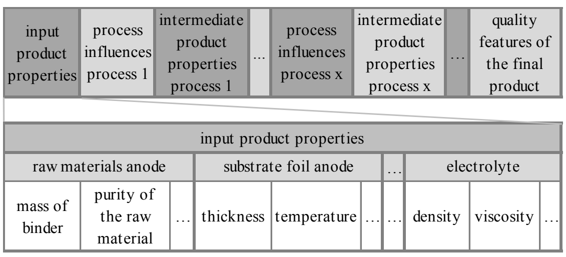

Figure 2: Example for a domain structure

The domains *process influences* are further differed in the categories *process parameters* and *disturbance quantities*. The second layer of the domain *intermediate product properties* consists of intermediate product names, like *slurry anode*. The third level includes the properties themselves, like *viscosity*. The quality features of the final product, the last domain of the MDM, are categorised in performance, geometry, safety and lifetime and further detailed in the third layer. Consequently, the structure of the production chain of lithium-ion cells as presented in [1] is completely mapped in the MDM. In order to obtain a symmetric matrix, the row and column labels of the MDM are identical. The MDM was generated and the values were filled into the MDM using MATLAB®. Therefore, the entries of the correlation matrices of each process were transferred to the MDM.

3.4. Computation of indirect correlations

Employing the generated MDM, the indirect cause-and-effect chains were calculated. For this purpose, two possible computation methods were identified: matrix multiplication and path search. Using the matrix multiplication the values of each cell have to be scaled during each multiplication, as the information needed for the scaling is lost after each multiplication step. In contrast, path search is based on Graph Theory [18]. Its computation method is similar to propagation trees [19]. First, every possible path between two elements is identified. Second, a mean value M_B for the severity of each path is generated according to equation 3, where m represents the number of process steps involved in the path. Since several paths between two elements can exist, the path with the highest mean severity M_B is selected for the further procedure.

$$M_B = \frac{\sum_{i=1}^{m} B_i}{m} \tag{3}$$

In Figure 3 the path search is illustrated on an example for the computation of the indirect dependency between element C1 and F11 and in Figure 4 the dependency set notation of the according computation is given. Grey values in Figure 3 are the derived indirect dependencies whereas black values represent the severity values B of the direct correlations obtained from the FMEA survey.

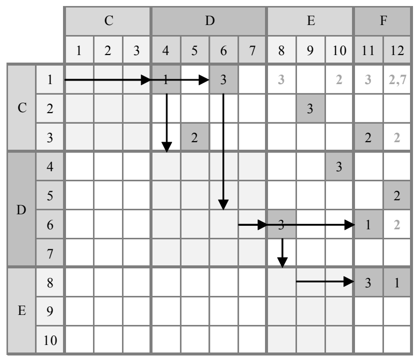

Figure 3: Strategy of the path search for indirect correlations

In Figure 4 s() indicates the existing direct dependencies from an element. In order to find all possible paths from C1 to F11, every direct dependency from C1 is considered. In this example C1 affects D4 and D6. D4 influences E10, but E10 has no further connections, so this path is irrelevant in this context. D6 affects the elements E8 and F11. Hence, one solution is the path C1-D6-F11 with a mean severity of 2. As E8 also influences F11 another solution is the path C1-D6-E8-F11 with a mean severity of 3. As the second path has the highest mean severity, its severity value is entered in the MDM as the indirect cause-and-effect of element C1 on element F11. Feedback loops cannot appear as a result of the sequential production chain mapped in the structure of the MDM.

Path C1 - F11
s(C1)= {D4, D6}
s(D4)= {E10}
s(E10)= {}
s(D6)= {E8, F11}
→ path(1)= C1-D6-F11
→ M(C1-D6-F11)= M_1= 2
s(E8)= {F11, F12}
→ path(2)= C1-D6-E8-F11
→M(C1-D6-E8-F11)= M_2= 3
Max(M_1, M_2)= M_2 = 3
→ indirect severity B(C1-F11)= 3

Figure 4: Dependency set notation of an exemplary path search

4. Classification of quality influences

Based on the derived indirect dependencies, the intermediate product properties can be classified [1]. Properties of category 3 have no influence on the quality features of the final product, whereas properties of category 2 influence quality features via indirect cause-and-effect chains. Properties of category 1 directly influence the quality features of the final product. If properties directly as well as indirectly influence the quality of the final product, they are also assigned to category 1. This categorisation can be done easily by means of the MDM entries in the domain *quality features of the final product*. If an entry exists in a column of the severity matrix, the element is assigned to category 1, whereas an entry in the matrix of the indirect dependencies reveals elements of category 2. All other elements are assigned to category 3 and are ignored for further analysis and removed from the MDM.

In Table 1 a summary of the evaluated data within this method in terms of the number of input parameters and of MDM dimensions is given. For the interpretation of the resulting matrices several classification figures exist [5]. For example Figure 5 shows the normalised active sum of the combined direct and indirect influences on the sixteen quality features. The active sums are normalised to 3 according to the highest evaluation value in the expert survey. In this context, elements with a high active sum strongly influence the quality of lithium-ion cells. In Figure 5 the influences assigned to the horizontal axis are arranged in the groups *input product properties*, *electrode production* and *cell assembly*. Clearly, most influences originating from electrode production have a high effect on cell quality. On the other hand, the effect strengths of cell assembly processes are wide spread. Nevertheless, considering the cell stacking or the electrolyte filling there are specific process parameters and intermediate product properties with strong influences on cell quality.

Table 1: Summary of evaluated data within this method

	quantity
Process influences	200
Intermediate/input product properties	194
Quality features of final product	16
Collected cause-and-effect correlations	2165
MDM dimensions	580
Elements without quality influence (category 3)	57

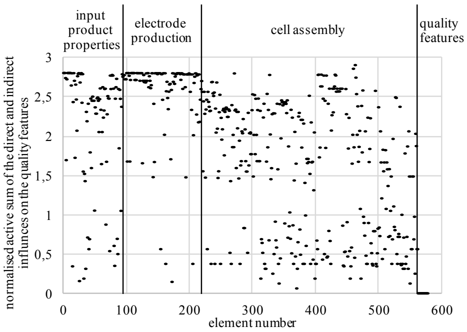

Figure 5: Active sum of the direct and indirect effects on the quality features

5. Method for Quality Parameter Selection

5.1. Overview and structure

The aim of this method is to extract the truly quality relevant influence quantities out of the amount of quantities listed in the MDM model 1, the output of the method described in the previous chapter. Furthermore, the cause-and-effect correlations in the production chain are to be quantified. For this purpose, the method is divided in two columns as shown in Figure 6: the *reduction* on the left and the *validation* on the right. These columns are iterated until the final MDM model contains the desired state of information, which ideally is reached after two iterations, implying that validation phase I and II are accomplished successfully (see section 5.3.). The iteration begins in the column *reduction*, where the initial MDM size is reduced in a two step procedure and indirect correlations are recalculated. The first step of reduction employs a Pareto analysis, the second is based on expert knowledge about the variability and the measurability of the MDM elements (see section 5.2.). The reduced MDM is then used to derive correlations and interaction matrices for each process, representing the interface between both columns. These matrices are the basis for the Design of Experiments (DoE) in the column *validation*. According to section 5.3 the experimental validation of the correlations is subdivided in two phases. Experimental data is statistically evaluated and the obtained results are transferred back to the MDM, generating its version x+1. From this point, the iteration starts all over.

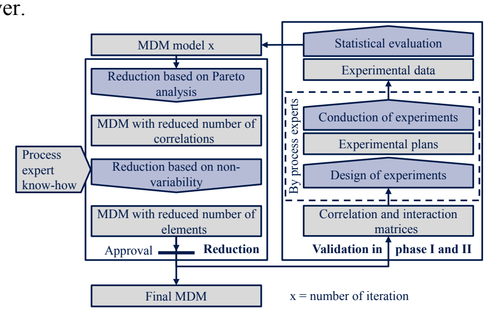

Figure 6: Structure of the method for quality parameter selection

5.2. Reduction and selection of quality influences

The first step of the reduction is a Pareto analysis conducted to exclude unimportant cause-and-effect correlations in the production chain. For this purpose, the risk was defined as the product of the probability A and the severity B. In order to consider only the most confident information, it was decided that the according levels of confidence S_A and S_B of the particular correlation are supposed to be higher than 2.5. The calculated risk values are combined in groups of equal risks and transferred to a two dimensional Pareto-diagram, in which one axis is assigned to the numbered elements in the groups, beginning with the groups with the highest risk, and the other axis shows the risk of an element as well as the aggregated relative share on the risk of all considered elements. The correlations responsible for the least 5% of the aggregated relative share were excluded, which corresponds to the amount C of the Pareto analysis. Basically, the thresholds for the reduction can be chosen freely. In this application, the first iteration of the reduction was meant to be conservative, since the matrix entries are based on expert knowledge up to now.

The second step of the reduction is based on the variability of the remaining process parameters and input product properties in the MDM as well as on the measurability of the product properties. Process experts prioritised these influences according to their subjective importance respectively to the principle possibility of variation in the upcoming experimental phase. In combination with a process chain wide examination by means of the MDM this information allows to identify intermediate product properties, which cannot be modified, since their influences are held constant. Consequently, these intermediate product properties as well as the non-variable process parameters and input product properties are not part of designed experiments. The product properties are also evaluated according to their measurability. Properties which cannot be measured are excluded. Moreover, in accordance with the scope of the methodology, correlations at the very beginning of cause-and-effect chains are also excluded, if they are not production induced [1].

To complete this method, correlation matrices for each process (see Figure 7) are generated based on the reduced information in the MDM, which represent the interface to the experimental phase. These matrices contain important information for the DoE, as there were: the selected input and output quantities of each process, the correlations of those, information about their variability, as well as the measurability of the intermediate product properties. The latter information can be based on the *detection* value from the FMEA or it has to be obtained from process experts. Besides the correlation matrices, a matrix for each process containing the interactions is generated from the FMEA data.

The reduction is finalised by a feedback loop to the process experts for the approval of the correlation and interaction matrices of each process for the experimental phase.

variability	execution of measurement	destructive measurement						
variability					1	1	1	1
	execution of measurement				1	1	0	1
		destructive measurement			0	1	1	0
					coating-thickness	coating-solvent	coating-homogeneity	coil straightness
1	1	0	input product property	carrier foil-width	0	1	0	0
0	1	1	input product property	carrier foil-hardness	0	1	0	2
1	1	0	intermediate product property	coating-thickness	3	0	0	0
1			process influences	line load	3	1	3	2
1			process influences	densification rate	3	1	3	0

Figure 7: Extend of a correlation matrix for the process *calendering*

5.3. Experimental validation

In the experimental phase the information contained in the MDM is validated and further process knowledge is built up empirically. The experimental validation is divided in two phases. Phase I plans the experiments for the validation of the assumed correlations in each process. Further goal of phase I is to increase knowledge of each process in order to support the following experimental investigations. Phase II validates process chain wide correlations. Its goal is to enable pre-defined process chain sections to produce intermediate products with the desired factor levels for subsequent process chain section experiments. Due to the sequential character of the process chain, it is likely that the first processes already begin with phase II, while the later processes are still employed with phase I (Figure 8).

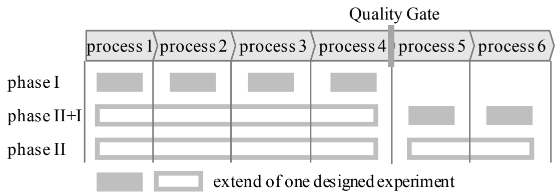

Figure 8: Phases of the experimental validation

In phase I only the variable process influences and their effects are of interest. The input product properties cannot be part of the experimental design, since in most cases the pre-process is not able to provide defined factor levels of those quantities. Consequently, they either have to be kept constant or to be measured in order to consider their effect in the experimental evaluation. If there are blocks of parameters which influence different intermediate product properties, several separate designs can be planned. In general, a fractional factorial design with two or three factor levels is recommended for phase I, depending on the restrictions regarding the number of experiments. Since in phase I no correlations between processes are investigated, know-how for single processes can be collected independent from other processes, e.g. already during commissioning of the individual production systems. However, in the sequential production chain of battery cells a forward oriented start-up of the processes in phase I is reasonable to ensure intermediate product supply. Based on the chosen experimental design measurement plans are to be generated, which describe in what experiment which intermediate product properties have to be measured. Especially in case of destructive or time or cost extensive measurements only the measurements required for the evaluation are conducted. An individual process finished phase I, if all process influences given in the process correlation matrix were investigated. Considering the variable process parameters, employing a fractional factorial design with two factor levels and centre points, lead to a manageable number of experiments for the entire production chain in phase I (Table 2).

Table 2: Summary of first reduction iteration and planned validation at *iwb*

	quantity
Correlations excluded in Pareto analysis	92
Non-variable process parameters	73
Non-variable input product properties	75
Resulting non-variable intermediate product prop.	39
Experiments in electrode production (phase I)	98
Experiments in cell assembly (phase I)	320

Phase II of the experimental validation concentrates on production chain sections in opposite to phase I which was focused on individual processes. Within a production chain section of phase II all influence parameters of a section are mapped on the intermediate product properties at the output of this section. So the experimental design in phase II regards the production chain sections as black boxes. The sectioning of the production chain as well as the measurement of the intermediate product properties between the sections is solved by means of *quality gates*. The position of the quality gates is determined considering the following issues:

- Desired number of quality gates corresponding to the black box character of the investigation
- Inline measurement systems
- Measurement effort corresponding to the number of quality gates and the number of intermediate product properties at the gate
- Possible number of experiments
- Intermediate products which can be outsourced

The minimal number of experiments for the entire production chain can be determined by an optimisation algorithm varying the number of quality gates and their position and taking the experimental as well as the measurement effort into account. If a production chain section is ready to begin with phase II, but the previous production chain section is not able to produce intermediate products with predefined factor levels, investigations can start with the process parameters and later examine the effects of the intermediate product properties. Phase II is completed when all correlations provided in the correlation matrix of a production chain section were investigated. When all production chain sections finished phase II, the cause-and-effect chains of interest, according to the chosen black box level and to the number of quality gates, can be evaluated up to the final product. In the production chain for lithium-ion cells at *iwb*, two quality gates have been chosen additionally to the final quality check-up: one after the electrode production and one before encasing the cell stack. Electrode production is equipped with powerful inline measurement systems. Besides, electrode material can be outsourced allowing an independent investigation of electrode production and cell assembly. The position of the second quality gate was motivated by the measurement effort. After the encasing of the cell stack most intermediate product properties would require destructive measurements. Consequently, the experimental design of the last production chain section maps the intermediate product properties of the ultrasonic-welded cell stack and the process parameters of case welding respectively sealing, of electrolyte filling and of pre-charging on the quality features of the finished lithium-ion cells.

On the one hand, the detailed experimental design, like the choice of the plan, its resolution or the number of factor levels, is left to the process experts. On the other hand, the method defines the minimal experimental requirements in order to investigate production chain wide cause-and-effects. Furthermore, the method supports the process experts in their experimental design by a structured procedure and by the aggregation of expert knowledge in the process specific correlation and interaction matrices.

6. Conclusion and Outlook

This paper detailed two novel methods as part of the overall methodology *quality planning of complex production chains for battery cells*. Starting with the evaluation of the FMEA-based expert surveys the method for quality parameter classification built a MDM of the entire production chain of lithium-ion cells mapping cause-and-effect chains up to the final product quality features. Based on the initial MDM model the method for quality parameter selection validates, quantifies and extracts truly quality relevant influence variables by means of an iteration of theoretical reduction and experiments. The updating procedure of the MDM itself, e.g. with the results of a statistical evaluation of the experimental data, represents the current state of research. Afterwards, the updated MDM can be used directly for an improved quality planning of complex production chains. Moreover, it can be part of a subsequent multivariate production chain optimization in order to improve product quality and to provide set-point values for the individual processes.

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